Sales demand forecasting in a textile factory using artificial neural network

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Abstract

Sales demand forecasting is an important issue for manufacturing companies. Indeed, such forecasting is decisive in the management of the production systems. This work compares the performance of an Artificial Neural Network to traditional methods in forecasting the sales demand in a textile factory over a reduced data set.

Keywords: Forecasting, Artificial Neural Network, Demand

Introduction

Demand forecasting is an important issue for manufacturing companies (Danese and Kalchschimidt, 2011). It can affect several areas of the company. Indeed, such forecasting is decisive in the management of the production systems as inventory management and production planning (Danese and Kalchschimidt, 2011).

Demand forecasting has been successfully applied in several sectors of the industry as well as economic (Tan, 2010) and financial systems (Healy et al., 2003).

Focusing on manufacturing systems, production systems and supply chain, several studies explore demand forecast using traditional statistical techniques (Danese and Kalchschimidt, 2011), (Dekker et. al., 2004) and (Babai et. al., 2013).

A very important negative event related to a bad forecasting method is the Bullwhip Effect (Jaipuria and Mahapatra, 2014). The bullwhip effect causes instability in the supply chain, since a small change in orders received by a retailer can result in larger changes in the resulting orders received by a factory. It costs money, wastes resources and results in a loss of market share (Wright and Yuan, 2008).

It is possible to use soft computing applied to demand forecasting, for both long-term and short-term forecasting. Among several techniques, Artificial Neural Networks (ANN) has been widespread to solve prediction and forecasting problems. In an assessment cited in (Kourentzes, 2014) it was concluded that the ANN outperforms the traditional forecasting methods in 73% of the cases.

Recurrent ANN is successfully applied to forecasting problems. Among several recurrent ANN topologies are the Multilayer Perceptron (MLP) and Elman ANN (Tan, 2010). This work aims at applying Elman ANN (ENN) to forecast the sales demand in a textile factory. The performance is compared to the real sales data and the factory specialist. The quality of the forecasting was analyzed over a reduced historical data.

Case Study

The ENN was applied to the sales forecasting in a textile industry. That factory produces several types of fabrics and the forecasting process consists in the definition of the quantity of fabric available for sales in the next month. The decision for this quantity is defined from the specialists in three steps: 1) market evaluation; 2) first meeting for sales forecasting and 3) adjustment period. Figure 1 presents the forecasting process of the factory. Considering a period of 35 months, Figure 2 presents the real sales and the forecasting sales from the factory specialists. The data set is a monthly register of the last three years, generating 35 records of real sales. This is a poor data set for applying statistical methods. This motivated the use of ANN in this study.

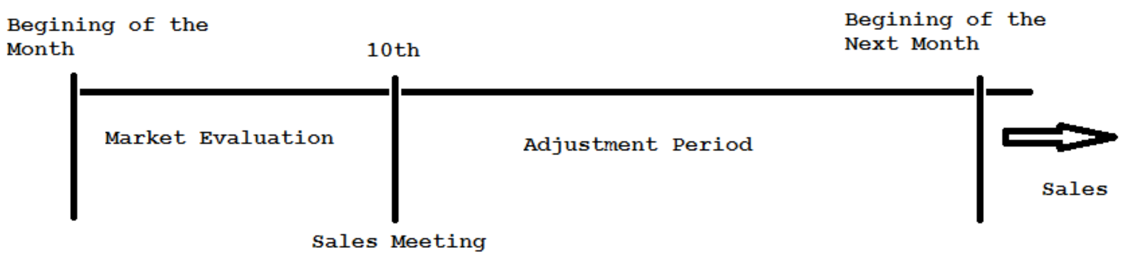

Figure 1 – Specialist forecasting process

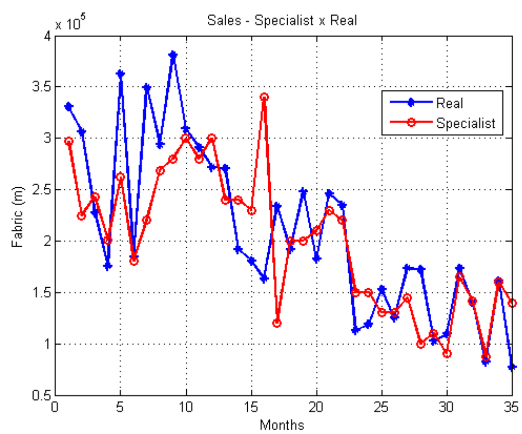

Figure 2 – Real sales versus specialist forecasting

Results

Some simulations were carried out using Matlab software to evaluate the performance of the ENN to forecast the sales demand. For such a task, the data set was divided into three groups: the training data set, the validation data set and the forecasting data set. From the amount of 35 values of real sales, 25 values were used for training, 5 for validation and 5 to test the forecasting ability of the network.

The simulations were performed, considering the forecasting period, using static and dynamic forecast. Static forecast uses the real past sales as input to forecast the sales in the next month. On the other hand, the dynamic forecast uses the past forecasted sales to forecast the sales in the next month. Figure 3 presents the forecasting result of the static network and Figure 4 presents the same result for the dynamic network.

Table 1 presents the sum of the mean squared error (MSE) from the specialists, and the static and dynamic forecast from the ENN. The dynamic forecasting presented a higher MSE than the static forecasting as expected.

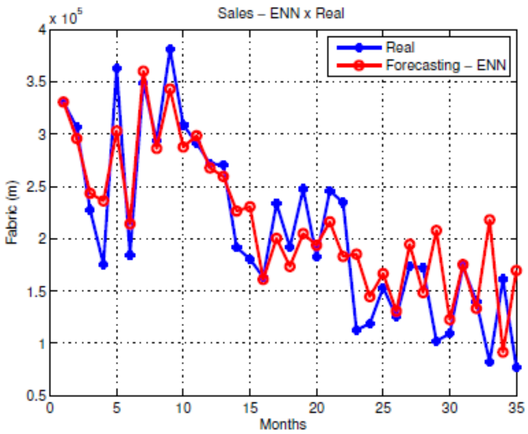

Figure 3 – Static forecasting

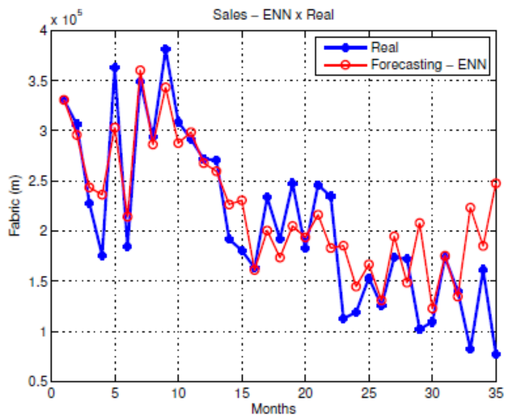

Figure 4 – Dynamic forecasting

Table 1 – Mean Squared Error (MSE)

Model	MSE
Specialist	3.2659e9
ENN (Static)	2.0527e9
ENN (Dynamic)	2.5567e9

Conclusions

This paper presented sales demand forecasting based on Elman Neural Networks (ENN). The forecasting is applied to a textile industry where a specialist group is responsible for the sales forecasting. It is clear from the results that the ENN can forecast the sales series with lower error than the specialist group. Hybrid computational intelligence methods can be applied in the future to improve forecasting performance.

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